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REGULARITY IN MONGE'S MASS TRANSFER PROBLEM

QI-RUI LI, FILIPPO SANTAMBROGIO, AND XU-JIA WANG

ABSTRACT. In this paper, we study the regularity of optimal mappings in Monge's mass transfer problem. Using the approximation to Monge's cost function $c(x, y) = |x - y|$ through the costs $c_\varepsilon(x, y) = \sqrt{\varepsilon^2 + |x - y|^2}$, we consider the optimal mappings T_ε for these costs, and we prove that the eigenvalues of the Jacobian matrix DT_ε , which are all positive, are locally uniformly bounded. By an example we prove that T_ε is in general not uniformly Lipschitz continuous as $\varepsilon \rightarrow 0$, even if the mass distributions are positive and smooth, and the domains are c -convex.

1. INTRODUCTION

The Monge mass transfer problem consists in finding an optimal mapping from one mass distribution to another one such that the total cost is minimized among all measure preserving mappings. This problem was first proposed by Monge [27] and has been studied by many authors in the last two hundred years: among the main achievements in the 20th century we cite [21] and [16].

In Monge's problem, the cost of moving a mass from point x to point y is proportional to the distance $|x - y|$, namely the cost function is given by

$$(1.1) \quad c_0(x, y) = |x - y|.$$

This is a natural cost function. In the last two decades, due to a range of applications, the optimal transportation for more general cost functions has been a subject of extensive studies. In order to present the framework more precisely, let Ω and Ω^* be two bounded domains in the Euclidean space \mathbb{R}^n , and let f and g be two densities in Ω and Ω^* respectively, satisfying the mass balance condition

$$(1.2) \quad \int_{\Omega} f(x) dx = \int_{\Omega^*} g(y) dy.$$

Let c be a smooth cost function defined on $\Omega \times \Omega^*$.

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The problem consists in finding a map $T : \Omega \rightarrow \Omega^*$ which solves

$$\min \int c(x, T(x))f(x)dx \quad : \quad T_{\#}f = g,$$

where the last condition reads “the image measure of f through T is g ” and means $\int_A g(y)dy = \int_{T^{-1}(A)} f(x)dx$ for all subsets $A \subset \Omega^*$.

The existence and uniqueness of optimal mappings were obtained in [4, 7, 20] if the cost function c satisfies

$$\text{(A)} \quad \forall (x_0, y_0) \in \Omega \times \Omega^*, \text{ the mappings } x \in \overline{\Omega} \rightarrow D_y c(x, y_0) \text{ and } y \in \overline{\Omega}^* \rightarrow D_x c(x_0, y) \text{ are diffeomorphisms onto their ranges.}$$

The regularity of optimal mappings was a more complicated issue. For the quadratic cost function, it reduces to the regularity of the standard Monge-Ampere equation, of which the regularity has been studied by many authors (see for instance [5, 6]). For general costs, the regularity was obtained in [26] if the domains satisfy a certain convexity condition, f, g are positive and smooth, and the cost function c satisfies the following structure condition

$$\text{(B)} \quad \forall x \in \overline{\Omega}, y \in \overline{\Omega}^*, \text{ and vectors } \xi, \eta \in \mathbb{R}^n \text{ with } \xi \perp \eta, \\ \sum_{i,j,k,l,p,q,r,s} \xi_i \xi_j \eta_k \eta_l (c_{ij,rs} - c^{p,q} c_{ij,p} c_{q,r,s}) c^{r,k} c^{s,l}(x, y) \geq \beta_0 |\xi|^2 |\eta|^2,$$

where β_0 is a positive constant. Loeper [24] showed that the optimal mapping may not be continuous if the condition **(B)** is violated, i.e. when there exist $\xi, \eta \in \mathbb{R}^n$ with $\xi \perp \eta$ such that the left hand side is negative. There are many follow-up researches on the regularity, in both the Euclidean space [23, 33] and on manifolds [2, 12, 18, 22, 25]. See also [31] for recent development.

Monge’s mass transfer problem is a prototype of the optimal transportation and the function (1.1) is the natural cost function. Therefore the existence and regularity of optimal mappings for Monge’s problem are of particular interest. However this cost function does not satisfy both key conditions, namely the condition **(A)** for the existence and the condition **(B)** for the a priori estimates.

The existence of optimal mappings for Monge’s problem has been studied by many researchers and was finally proved in [8, 32]. Prior to that, the existence was also obtained in [16] under some assumptions, and obtained in [30], with a gap fixed in [1]. See also [3, 9, 10] for the existence of optimal mappings when the norm (1.1) is replaced by a more general norm in the Euclidean space. The proofs in [8, 32] are very similar: both use the approximation $|x - y|^{1+\varepsilon} \rightarrow |x - y|$ ($\varepsilon \rightarrow 0$). The key point is choosing an approximation with strictly convex costs of the difference $x - y$, which satisfy the

assumption **(A)**. The optimal mapping for Monge's problem is not unique in general. But there is a unique optimal mapping which is monotone on the transfer rays [17].

In this paper we study the regularity of optimal mappings in Monge's mass transfer problem. As the cost function (1.1) does not satisfy condition **(B)**, the argument in [26] does not apply to Monge's problem. Indeed, Monge's problem also admits several minimizers T , even if a special one plays an important role: it is the transport map which is monotone on each transport ray (see [1]: we will call this map monotone optimal transport).

The regularity seems a rather tricky problem and very little is known at the moment. Only in the 2 dimensional case, it was proved in [19] that the monotone optimal mapping is continuous in the interior of the transfer set (i.e. the union of all transfer rays), under the assumptions that the densities f, g are positive, continuous, and with compact, convex and disjoint supports.

Our strategy to attack the regularity in Monge's problem is to establish uniform estimates for the optimal mappings with respect to the cost function

$$(1.3) \quad c_\varepsilon(x, y) = \sqrt{\varepsilon^2 + |x - y|^2}$$

where $\varepsilon \in (0, 1]$ is a constant. The cost function c_ε satisfies both conditions **(A)** and **(B)**. Therefore there is a unique optimal mapping T_ε associated with c_ε , given by

$$T_\varepsilon(x) = x - \frac{\varepsilon Du_\varepsilon}{\sqrt{1 - |Du_\varepsilon|^2}}.$$

where u_ε is the potential function. By direct computation, u_ε satisfies the Monge-Ampère equation [26]

$$(1.4) \quad \det w_{ij} = \frac{1}{\varepsilon^n} \left[1 - |Du|^2 \right]^{\frac{n+2}{2}} \frac{f}{g},$$

with

$$\{w_{ij}\} = \left\{ \frac{\sqrt{1 - |Du|^2}}{\varepsilon} (\delta_{ij} - u_{x_i} u_{x_j}) - u_{x_i x_j} \right\}.$$

Under appropriate assumptions, the a priori estimate

$$(1.5) \quad \sup_{\Omega'} |D^2 u_\varepsilon(x)| \leq C_\varepsilon \quad \forall \Omega' \subset\subset \Omega.$$

was established in [26], where the upper bound C_ε depends on ε . Notice that the assumptions involve in particular lower bounds on the densities f and g on their respective domains $\bar{\Omega}$ and $\bar{\Omega}^*$. these domains should be c_ε -convex w.r.t. each other, which typically reduces (if we want to impose it for all $\varepsilon \rightarrow 0$) to the case of $\Omega \subset \Omega^*$, with Ω^* convex. In particular, this rules out the assumption of [19], since the supports will not be disjoint. The case we study is thus completely different from that of [19].

Equation (1.4) is strongly singular as $\varepsilon \rightarrow 0$. Note that, due to the small ε , a uniform bound for D^2u_ε does not mean a uniform estimate for the optimal mapping T_ε . Therefore we need to work directly on the mapping T_ε .

We wished to prove a uniform bound for DT_ε , namely the uniform Lipschitz continuity of the optimal mapping T_ε . By tedious computations, we are able to prove that all the eigenvalues of the matrix DT_ε , which are all positive, are locally uniformly bounded as $\varepsilon \rightarrow 0$. This is one of the two main results of the paper. Notice that this should bring some information on the behavior of DT_0 , where T_0 is the monotone optimal mapping in Monge's problem. Yet, two problems arise: i) the condition on the eigenvalues being strongly nonlinear and applied to non-symmetric matrices, it is not easy to pass it to the limit, nor to give a meaning to the eigenvalues of DT_0 (which is a priori a distribution); ii) even the fact that the maps T_ε do converge to the monotonic optimal transport is not that easy if the supports of the measures are not disjoint (which is not the case for us).

However, as the matrix DT_ε is - as we said - not symmetric, the boundedness of the eigenvalues of DT_ε does not imply the matrix itself is uniformly bounded. Interestingly, we find that the matrix DT_0 is not bounded in general. There exist positive and smooth f, g such that DT_0 is unbounded at interior points (here by T_0 we mean the monotonic Monge optimal transport, and not the limit of T_ε ; however, it is possible to prove (see Section 4) that, should DT_ε be bounded, then $T_\varepsilon \rightarrow T_0$, and hence this implies that DT_ε cannot be uniformly bounded as $\varepsilon \rightarrow 0$). This is the second main result of the paper.

This paper is arranged as follows. In section 2, we state our main estimate, Theorem 1. Section 3 is then devoted to the proof of Theorem 1. In section 4, we provide positive and smooth densities f, g such that the monotonic optimal mapping T_0 is not Lipschitz continuous at interior points. We conclude the paper with some remarks and perspectives in Section 5.

2. UNIFORM A PRIORI ESTIMATES

Let $c = c_\varepsilon$ be the cost function given in (1.3). The optimal mapping $T = T_\varepsilon : \Omega \rightarrow \Omega^*$ is given by [26]

$$(2.1) \quad T(x) = [D_x c(x, \cdot)]^{-1} Du(x),$$

where $u = u_\varepsilon$ is a c -concave potential function. In this and the next sections, we deal with the a priori estimates for DT . We will omit the subscript ε when no confusions arise.

From [26], the potential function u satisfies the fully nonlinear PDE of Monge-Ampère type,

$$(2.2) \quad \det(D_x^2 c - D^2 u) = |\det D_{xy}^2 c| \frac{f}{g \circ T} \text{ in } \Omega.$$

For the cost function (1.3), one has

$$(2.3) \quad Dc(x, y) = \frac{x - y}{\sqrt{\varepsilon^2 + |x - y|^2}}.$$

Hence by (2.1),

$$(2.4) \quad T(x) = x - L(x)Du(x),$$

where the function L is given by

$$(2.5) \quad L(x) =: \frac{\varepsilon}{\sqrt{1 - v}}$$

and

$$(2.6) \quad v =: |Du|^2.$$

From (2.4) and (2.5), we can solve

$$(2.7) \quad v = \frac{d^2(x)}{\varepsilon^2 + d^2(x)}$$

and consequently

$$(2.8) \quad L = \sqrt{\varepsilon^2 + d^2(x)},$$

where

$$(2.9) \quad d(x) = |x - T(x)|.$$

As in [26], we denote

$$(2.10) \quad \begin{aligned} A_{ij}(x) &= D_{x^i x^j}^2 c(x, T(x)) \\ &= \frac{1}{L} (\delta_{ij} - D_i u D_j u). \end{aligned}$$

Then equation (2.2) can be written in the form

$$(2.11) \quad \det w_{ij} = \frac{\varepsilon^2}{L^{n+2}} \frac{f}{g \circ T},$$

where

$$(2.12) \quad w_{ij} =: A_{ij} - D_{ij}^2 u$$

is a nonnegative symmetric matrix.

We observe from (2.10) that A_{ij} is positive definite, and the inverse matrix of A_{ij} is given by

$$(2.13) \quad A^{ij} = L\left(\delta_{ij} + \frac{L^2}{\varepsilon^2} D_i u D_j u\right).$$

Let us denote

$$(2.14) \quad W =: \sum_{\alpha, \beta=1}^n A^{\alpha\beta} w_{\alpha\beta}.$$

Then we have following uniform estimates:

Theorem 1. *Suppose Ω, Ω^* are bounded domains in \mathbb{R}^n ($n \geq 2$), $f \in C^{1,1}(\Omega), g \in C^{1,1}(\Omega^*)$, f, g have positive upper and lower bounds, and (1.2) holds. Let $u \in C^{3,1}(\Omega)$ be a c -concave solution to (2.11), then we have a priori estimate*

$$(2.15) \quad W(x) \leq C,$$

where C depends on $n, \text{dist}(x, \partial\Omega)$, f and g , but is independent of the constant $\varepsilon \in (0, 1]$.

By (2.4) (2.12) and (2.13), it is ready to check that the Jacobian matrix of T is given by

$$(2.16) \quad \begin{aligned} T_j^i &= \delta_{ij} - L_j u_i - L u_{ij} \\ &= \delta_{ij} - L\left(u_{ij} + \frac{L^2}{\varepsilon^2} u_i \sum_k u_k u_{kj}\right) \\ &= \sum_k A^{ik} w_{kj}. \end{aligned}$$

Since the matrices $\{A^{ij}\}$ and $\{w_{ij}\}$ are positive, then DT is diagonalizable, and its eigenvalues $\lambda_1, \dots, \lambda_n$ of Jacobian DT are positive, and $\sum_{i=1}^n \lambda_i = W$. So if W is bounded, one immediately sees that all the eigenvalues of DT are bounded from above and below. We therefore have

Corollary 1. *Under the assumptions of Theorem 1, we have for any $\Omega' \subset\subset \Omega$,*

$$(2.17) \quad C^{-1} \leq \min_i \lambda_i \leq \max_i \lambda_i \leq C \quad \text{in } \Omega',$$

where C depends on $n, \text{dist}(\Omega', \partial\Omega)$, f and g , but is independent of $\varepsilon \in (0, 1]$.

In view of (2.13) and (2.14), one finds that

$$W = L \sum_i w_{ii} + \frac{L^3}{\varepsilon^2} \sum_{i,j} u_i u_j w_{ij}.$$

Hence we obtain

$$L \sum w_{ii} \leq C$$

By (2.10) and (2.12), we also obtain the estimate for D^2u .

Corollary 2. *Under the assumptions of Theorem 1, we have for any $\Omega' \subset\subset \Omega$,*

$$(2.18) \quad |D^2u| \leq C/L \text{ in } \Omega',$$

where C depends on n , $\text{dist}(\Omega', \partial\Omega)$, f and g , but is independent of $\varepsilon \in (0, 1]$.

Corollary 2 morally gives a $C^{1,1}$ estimate for the potential function $u_0 = \lim_{\varepsilon \rightarrow 0} u$ on the set

$$E_\delta = \{x \in \Omega : |T(x) - x| \geq \delta > 0\}.$$

This recovers a well-known result which reads “the potential is $C^{1,1}$ in the interior of transport rays”, which was also used by [1] in order to prove the countable Lipschitz property of the direction of Du . At a point x_0 with $v(x_0) > 0$, denote

$$\nu = -\frac{Du(x_0)}{|Du(x_0)|},$$

and let ξ^α be unit vectors such that $\{\nu, \xi^\alpha\}_{\alpha=1, \dots, n-1}$ are orthonormal. We denote

$$\begin{aligned} T_\nu^\nu &= \sum_{i,j} \nu_i \nu_j T_j^i, \\ T_{\xi^\alpha}^{\xi^\alpha} &= \sum_{i,j} \xi_i^\alpha \xi_j^\alpha T_j^i. \end{aligned}$$

By (2.16) and (2.13),

$$(2.19) \quad \begin{aligned} D_\nu \langle \nu, T \rangle &= T_\nu^\nu = \sum_{i,j,k} \nu_i A^{ik} w_{kj} \nu_j \\ &= L \sum_{i,j,k} \left(1 + \frac{vL^2}{\varepsilon^2}\right) \nu_k w_{kj} \nu_j \\ &= \frac{L^3}{\varepsilon^2} \sum_{j,k} \nu_k w_{kj} \nu_j. \end{aligned}$$

Similarly,

$$(2.20) \quad D_{\xi^\alpha} \langle \xi^\alpha, T \rangle = T_{\xi^\alpha}^{\xi^\alpha} = L \sum_{j,k} \xi_k^\alpha w_{kj} \xi_j^\alpha.$$

Noticing that $\{w_{ij}\}$ is positive definite, it is clear from (2.19) and (2.20) that T_ν^ν and $T_{\xi^\alpha}^{\xi^\alpha}$ are positive. Recall that

$$W = T_\nu^\nu + \sum_{\alpha=1}^{n-1} T_{\xi^\alpha}^{\xi^\alpha}.$$

Hence by (2.15) we obtain

Corollary 3. *Under the assumptions of Theorem 1, we have for any $\Omega' \subset\subset \Omega$,*

$$(2.21) \quad \begin{cases} T_\nu^\nu \leq C \\ T_{\xi^\alpha}^{\xi^\alpha} \leq C \end{cases} \quad \text{in } \Omega',$$

where C depends on n , $\text{dist}(\Omega', \partial\Omega)$, f and g , but is independent of $\varepsilon \in (0, 1]$.

At the limit, this corresponds to saying (even if what we state here is not rigorous) that the limit mapping T_0 is Lipschitz continuous in the direction of transfer rays, and for any unit vector ξ perpendicular to the transfer rays, $\langle \xi, T_0 \rangle$ is Lipschitz continuous in the ξ -direction. The Lipschitz continuity along transport rays is not surprising, since we are doing one-dimensional optimal transport between two measures with upper and lower bounds on their densities; yet, the densities of the one-dimensional problem along each ray are affected by a Jacobian factor (due to the decomposition of f and g along rays), and this makes this Lipschitz result not completely evident. In section 4, we will construct an example to show that the component $\langle \nu_0, T_0 \rangle$ is in general not Lipschitz continuous in ξ , even though the mass distributions are positive and smooth, where ν_0 is a direction of transfer rays and $\xi \perp \nu_0$.

In Theorem 1, we assume that $u \in C^{3,1}$. This assumption is not needed if $\Omega \subset \Omega^*$ and Ω^* is a bounded convex domain in \mathbb{R}^n , as it implies that Ω^* is c^* -convex with respect to Ω and by approximation, and the condition $u \in C^{3,1}$ is always satisfied, see [26].

3. PROOF OF THEOREM 1

To prove Theorem 1, we introduce the auxiliary function

$$(3.1) \quad H(x) = \eta(x)W(x),$$

where η is a cut-off function. Suppose that H attains its maximum at some point x_0 . To prove that $H(x_0)$ is uniformly bounded in ε , the computation is rather complicated. We find the computation can be made a little simpler if we first make a linear transformation such that

$$(3.2) \quad A_{ij}(x_0) = \delta_{ij},$$

and then make a rotation of coordinates such that

$$(3.3) \quad w_{ij}(x_0) = \text{diag} \{ \lambda_1, \dots, \lambda_n \}.$$

It is well-known that A_{ij} , w_{ij} are tensors [22]. An advantage of working on tensors is that one may choose a particular coordinate system to simplify the computation. As we only made a linear transform on the Euclidean space \mathbb{R}^n , the Riemannian curvature tensor under the metric σ_{ij} vanishes, which allows us to exchange the derivatives freely. In the following we will use D to denote the normal derivatives in \mathbb{R}^n and ∇ to denote covariant derivatives under the metric σ .

Suppose the linear transformation is given by $y = P^{-1}x$ (i.e. $x_i = \sum P_{ik}y_k$) such that $P^TAP = I$ is the unit matrix at x_0 . Then by (2.10) and (2.12),

$$\begin{aligned}\bar{A}_{ij} &= \sum_{k,l} A_{kl}P_{ki}P_{lj} = (P^TAP)_{ij}, \\ \bar{w}_{ij} &= \sum_{k,l} w_{kl}P_{ki}P_{lj} = (P^TWP)_{ij},\end{aligned}$$

where bar denotes quantities in the y -coordinates.

Denote $\{\sigma_{ij}\} = P^TP$, and $\{\sigma^{ij}\} = (P^TP)^{-1}$. Then by (2.10) and (2.13),

$$\begin{aligned}(3.4) \quad \delta_{ij} &= \bar{A}_{ij} = (P^TAP)_{ij} \\ &= \frac{1}{L}(\sigma_{ij} - \bar{u}_i\bar{u}_j)\end{aligned}$$

and

$$\begin{aligned}(3.5) \quad \delta_{ij} &= \bar{A}^{ij} = (P^{-1}A^{-1}(P^T)^{-1})_{ij} \\ &= L(\sigma^{ij} + \frac{L^2}{\varepsilon^2}\bar{u}^i\bar{u}^j),\end{aligned}$$

where $\bar{u}^i =: \sum_k \sigma^{ik}\bar{u}_k$. Note that by (2.7) and (2.8), v and L are invariant under the coordinate transformation, and

$$(3.6) \quad \bar{v} = \sum \sigma^{ij}\bar{u}_i\bar{u}_j = \sum \bar{u}^i\bar{u}_i \leq 1,$$

$$(3.7) \quad \varepsilon^2 \leq \bar{L}^2 \leq C.$$

For simplicity we will omit the bar below. In view of (3.4), we have, at x_0 ,

$$(3.8) \quad \sigma_{ij} = L\delta_{ij} + \nabla_i u \nabla_j u.$$

By (3.5), we have, at x_0 ,

$$\begin{aligned}u_i &= \sum_j \delta_{ij}u_j \\ &= \sum_j L(\sigma^{ij} + \frac{L^2}{\varepsilon^2}u^i u^j)u_j \\ &= L(1 + \frac{L^2}{\varepsilon^2}v)u^i,\end{aligned}$$

where $u_i = \nabla_i u$. By (2.5), it follows that

$$(3.9) \quad u_i = \frac{Lu^i}{1-v} = \frac{L^3}{\varepsilon^2} u^i.$$

Hence $u^i = \frac{\varepsilon^2}{L^3} u_i$ and by (3.5),

$$(3.10) \quad \sigma^{ij} = \frac{1}{L} \left(\delta_{ij} - \frac{\varepsilon^2}{L^3} u_i u_j \right).$$

Formulas (3.8), (3.9) and (3.10) will be repeatedly used in our calculation below. Without loss of generality, we may also assume

$$(3.11) \quad \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$$

at x_0 .

Since x_0 is the maximum point, we have

$$(3.12) \quad \begin{aligned} 0 &= \nabla_i \log H(x_0) = \frac{\eta_i}{\eta} + \frac{W_i}{W} \\ &= \frac{\eta_i}{\eta} + \frac{\sum w_{\alpha\alpha;i}}{W} - \frac{\sum A_{\alpha\alpha;i} w_{\alpha\alpha}}{W}, \\ 0 &\geq \nabla_{ij}^2 \log H(x_0) = \frac{\eta_{ij}}{\eta} - 2 \frac{\eta_i \eta_j}{\eta^2} + \frac{W_{ij}}{W} \end{aligned}$$

as a matrix, where subscripts i, j on the R.H.S. denote covariant derivatives in the metric σ . We thus obtain, at x_0 ,

$$(3.13) \quad 0 \geq W \sum w^{ij} \left(\frac{\eta_{ij}}{\eta} - 2 \frac{\eta_i \eta_j}{\eta^2} \right) + \sum w^{ij} W_{ij},$$

where w^{ij} is the inverse of w_{ij} .

Differentiating (2.11) gives

$$(3.14) \quad \sum w^{ij} w_{ij;a} = \varphi_a,$$

$$(3.15) \quad \sum w^{ij} w_{ij;ab} = \sum w^{is} w^{jt} w_{ij;a} w_{st;b} + \varphi_{ab},$$

where φ is given by

$$(3.16) \quad \varphi = \log \left(\frac{\varepsilon^2}{L^{n+2}} \frac{f}{g \circ T} \right).$$

In our computation we use the notation $w_{ij;k} = \nabla_k w_{ij}$, $w_{ij;kl} = \nabla_l \nabla_k w_{ij}$, $A_{ij;k} = \nabla_k A_{ij}$ and $A_{ij;kl} = \nabla_l \nabla_k A_{ij}$.

To estimate the term $\sum w^{ij} W_{ij}$ in (3.13), we first prove the following lemma.

Lemma 1. *We have*

$$\begin{aligned} A_{ij;k} &= \frac{L^2}{\varepsilon^2} A_{ij} u^h w_{hk} + \frac{1}{L} (u_j w_{ik} + u_i w_{jk}) \\ &\quad - \frac{1}{L} (A_{ij} u_k + A_{ik} u_j + u_i A_{jk}), \\ A_{ii;\beta} - A_{i\beta;i} &= \frac{L^2}{\varepsilon^2} (A_{ii} u^t w_{t\beta} - A_{i\beta} u^t w_{ti}) + \frac{1}{L} (w_{i\beta} u_i - w_{ii} u_\beta), \end{aligned}$$

(we use the summation convention $u^h w_{hk} = \sum_h u^h w_{hk}$).

Proof. Recall that $v = \sigma^{ij} u_i u_j = \sum u^i u_i$. Therefore

$$\begin{aligned} \frac{dL}{dv} &= \frac{1}{2} \frac{L^3}{\varepsilon^2}, \\ v_k &= 2u^h u_{hk}. \end{aligned}$$

By (3.4), $A_{ij} = \frac{1}{L} (\sigma_{ij} - u_i u_j)$. Differentiating, we get

$$\begin{aligned} (3.17) \quad A_{ij;k} &= -\frac{1}{L^2} \frac{dL}{dv} v_k (\sigma_{ij} - u_i u_j) + \frac{1}{L} (-u_{ik} u_j - u_i u_{jk}) \\ &= -\frac{L^2}{\varepsilon^2} A_{ij} u^h u_{hk} + \frac{1}{L} (-u_{ik} u_j - u_i u_{jk}) \\ &= \frac{L^2}{\varepsilon^2} A_{ij} u^h w_{hk} + \frac{1}{L} (w_{ik} u_j + u_i w_{jk}) \\ &\quad - \frac{1}{L} (A_{ij} u_k + A_{ik} u_j + u_i A_{jk}). \end{aligned}$$

The second formula follows from (3.17) immediately. \square

Differentiating (2.14) twice and using $A_{ij}(x_0) = \delta_{ij}$,

$$\begin{aligned} (3.18) \quad \sum_{i,j} w^{ij} W_{ij} &= \sum w^{ij} w_{\alpha\alpha;ij} - 2 \sum w^{ij} A_{\alpha\beta;i} w_{\alpha\beta;j} - \sum w^{ij} A_{\alpha\alpha;ij} w_{\alpha\alpha} \\ &\quad + 2 \sum w^{ij} A_{\alpha k;i} A_{\beta k;j} w_{\alpha\beta} \\ &\geq \sum w^{ij} w_{\alpha\alpha;ij} - 2 \sum w^{ij} A_{\alpha\beta;i} w_{\alpha\beta;j} - \sum w^{ij} A_{\alpha\alpha;ij} w_{\alpha\alpha}. \end{aligned}$$

We have by (3.15)

$$\begin{aligned} (3.19) \quad \sum_{i,j,\alpha} w^{ij} w_{\alpha\alpha;ij} &= \sum w^{ij} A_{\alpha\alpha;ij} - \sum w^{ij} u_{\alpha\alpha ij} \\ &= \sum w^{ij} w_{ij;\alpha\alpha} + \sum w^{ij} (A_{\alpha\alpha;ij} - A_{ij;\alpha\alpha}) \\ &\geq \sum \varphi_{\alpha\alpha} + \sum w^{ii} (A_{\alpha\alpha;ii} - A_{ii;\alpha\alpha}). \end{aligned}$$

By the first formula in Lemma 1

$$\begin{aligned} \sum_{i,j,\alpha,\beta} w^{ij} A_{\alpha\beta;i} w_{\alpha\beta;j} &= \frac{L^2}{\varepsilon^2} \sum w_{\alpha\alpha;i} u^i - \frac{1}{L} \sum w^{ij} u_j w_{\alpha\alpha;i} \\ &\quad + \frac{2}{L} \sum u_\beta w_{\alpha\beta;\alpha} - \frac{2}{L} \sum w^{ij} u_\beta w_{j\beta;i}. \end{aligned}$$

By (3.9), it follows

$$\begin{aligned} \sum_{i,j,\alpha,\beta} w^{ij} A_{\alpha\beta;i} w_{\alpha\beta;j} &= 3 \frac{L^2}{\varepsilon^2} \sum w_{\alpha\alpha;i} u^i - \frac{1}{L} \sum w^{ij} u_j w_{\alpha\alpha;i} \\ &\quad + \frac{2}{L} \sum u_\beta (A_{\alpha\beta;\alpha} - A_{\alpha\alpha;\beta}) - \frac{2}{L} \sum w^{ij} u_\beta w_{ij;\beta} \\ &\quad - \frac{2}{L} \sum w^{ii} u_\beta (A_{i\beta;i} - A_{ii;\beta}). \end{aligned}$$

By (3.14) and the second formula in Lemma 1, we then obtain

$$\begin{aligned} \sum_{i,j,\alpha,\beta} w^{ij} A_{\alpha\beta;j} w_{\alpha\beta;i} &= 3 \frac{L^2}{\varepsilon^2} \sum w_{\alpha\alpha;i} u^i - \frac{1}{L} \sum w^{ii} u_i w_{\alpha\alpha;i} \\ &\quad - 2 \frac{L^2}{\varepsilon^2} \sum \varphi_\beta u^\beta + 2 \frac{Lv}{\varepsilon^2} (W - n) \\ &\quad + 2 \frac{L}{\varepsilon^2} (W - n) \sum w_{ii} u_i u^i, \end{aligned}$$

where

$$W =: \sum w^{ii} = \sum \frac{1}{\lambda_i}.$$

Recalling (3.9) and (3.6),

$$(3.20) \quad 0 \leq u^i u_i \leq \sum u^i u_i \leq 1$$

for any given i . Hence

$$(3.21) \quad \begin{aligned} \sum_{i,j,\alpha,\beta} w^{ij} A_{\alpha\beta;j} w_{\alpha\beta;i} &\leq 3 \frac{L^2}{\varepsilon^2} \sum w_{\alpha\alpha;i} u^i - \frac{1}{L} \sum w^{ii} u_i w_{\alpha\alpha;i} \\ &\quad - 2 \frac{L^2}{\varepsilon^2} \sum \varphi_\beta u^\beta + \frac{L}{\varepsilon^2} Q. \end{aligned}$$

Here and below we use Q to denote quantities satisfying

$$Q \leq C \left(1 + \frac{W}{\eta} + W^2 + \frac{1}{\eta} W \mathcal{W} \right).$$

Inserting (3.19) and (3.21) into (3.18), we obtain

$$(3.22) \quad \begin{aligned} \sum w^{ij}W_{ij} &\geq \sum w^{ii}(A_{\alpha\alpha;ii} - A_{ii;\alpha\alpha}) - \sum w^{ii}A_{\alpha\alpha;ii}w_{\alpha\alpha} \\ &\quad - 6\frac{L^2}{\varepsilon^2} \sum w_{\alpha\alpha;i}u^i + \frac{2}{L} \sum w^{ii}u_iw_{\alpha\alpha;i} \\ &\quad + \sum \varphi_{\alpha\alpha} + \frac{4L^2}{\varepsilon^2} \sum \varphi_{\alpha}u^{\alpha} - \frac{L}{\varepsilon^2}Q. \end{aligned}$$

To proceed further, we need the following lemma.

Lemma 2. *We have*

$$\begin{aligned} \sum_{i,\alpha} w^{ii}(A_{\alpha\alpha;ii} - A_{ii;\alpha\alpha}) &\geq \frac{L}{\varepsilon^2}\mathcal{W} \sum w_{ii}^2 - \frac{2}{L} \sum w^{ii}u_iw_{\alpha\alpha;i} \\ &\quad - \frac{L^2}{\varepsilon^2}\mathcal{W} \sum w_{\alpha\alpha;h}u^h + (n+2)\frac{L^2}{\varepsilon^2} \sum \varphi_{\beta}u^{\beta} - \frac{L}{\varepsilon^2}Q \end{aligned}$$

and

$$\begin{aligned} \sum_{i,\alpha} w^{ii}A_{\alpha\alpha;ii}w_{\alpha\alpha} &\leq -2\frac{L}{\varepsilon^2}\mathcal{W} \sum w_{ii}^2u_iu^i - \frac{L}{\varepsilon^2}\mathcal{W}\mathcal{W} \sum w_{ii}u_iu^i \\ &\quad + \frac{L^2}{\varepsilon^2}\mathcal{W} \sum \varphi_{\beta}u^{\beta} + \frac{2L^2}{\varepsilon^2} \sum w_{ii}u^i\varphi_i + \frac{L}{\varepsilon^2}Q. \end{aligned}$$

Proof. In view of Lemma 1,

$$(3.23) \quad A_{\alpha\alpha;i} = -\frac{L^2}{\varepsilon^2}A_{\alpha\alpha}u^hu_{hi} - \frac{2}{L}u_{\alpha}u_{\alpha i}.$$

By differentiating (3.23),

$$(3.24) \quad \begin{aligned} A_{\alpha\alpha;ii} &= -\frac{L^2}{\varepsilon^2}A_{\alpha\alpha}u^hu_{hii} - \frac{L^2}{\varepsilon^2}A_{\alpha\alpha}\sigma^{ht}u_{ti}u_{hi} \\ &\quad - \frac{L^2}{\varepsilon^2}A_{\alpha\alpha;i}u^hu_{hi} - 2\frac{L^4}{\varepsilon^4}A_{\alpha\alpha}u^tu_{ti}u^hu_{hi} \\ &\quad - \frac{2}{L}u_{\alpha}u_{i\alpha i} - \frac{2}{L}u_{i\alpha}^2 + \frac{2L}{\varepsilon^2}u^hu_{hi}u_{\alpha}u_{i\alpha}. \end{aligned}$$

Plugging (3.23) into (3.24), we infer that

$$\begin{aligned} A_{\alpha\alpha;ii} &= -\frac{L^2}{\varepsilon^2}A_{\alpha\alpha}u^hu_{i ih} - \frac{L^2}{\varepsilon^2}A_{\alpha\alpha}\sigma^{ht}u_{ti}u_{hi} \\ &\quad - \frac{L^4}{\varepsilon^4}A_{\alpha\alpha}u^tu_{ti}u^hu_{hi} - \frac{2}{L}u_{\alpha}u_{i\alpha i} \\ &\quad - \frac{2}{L}u_{i\alpha}^2 + \frac{4L}{\varepsilon^2}u^hu_{hi}u_{\alpha}u_{i\alpha}. \end{aligned}$$

By (3.10),

$$-\frac{L^2}{\varepsilon^2}A_{\alpha\alpha}\sigma^{ht}u_{ti}u_{hi} = -\frac{L}{\varepsilon^2}A_{\alpha\alpha}u_{ii}^2 + \frac{L^4}{\varepsilon^4}A_{\alpha\alpha}u_{ii}^2u^i u^i.$$

Hence

$$\begin{aligned}
A_{\alpha\alpha;ii} &= -\frac{L^2}{\varepsilon^2}A_{\alpha\alpha}u^h u_{iih} - \frac{L}{\varepsilon^2}A_{\alpha\alpha}u_{ii}^2 \\
&\quad - \frac{2}{L}u_{\alpha}u_{ii\alpha} - \frac{2}{L}u_{i\alpha}^2 + \frac{4L}{\varepsilon^2}u_{ii}u_{i\alpha}u_{\alpha}u^i \\
&= \frac{L^2}{\varepsilon^2}A_{\alpha\alpha}u^h w_{ii;h} - \frac{L^2}{\varepsilon^2}A_{\alpha\alpha}u^h A_{ii;h} - \frac{L}{\varepsilon^2}A_{\alpha\alpha}u_{ii}^2 \\
&\quad + \frac{2}{L}u_{\alpha}w_{ii;\alpha} - \frac{2}{L}u_{\alpha}A_{ii;\alpha} - \frac{2}{L}u_{i\alpha}^2 + \frac{4L}{\varepsilon^2}u_{ii}u_{i\alpha}u_{\alpha}u^i.
\end{aligned}$$

Employing (3.23) again, it follows

$$\begin{aligned}
(3.25) \quad A_{\alpha\alpha;ii} &= \frac{L^2}{\varepsilon^2}A_{\alpha\alpha}w_{ii;h}u^h + \frac{2}{L}u_{\alpha}w_{ii;\alpha} \\
&\quad - \frac{L}{\varepsilon^2}A_{\alpha\alpha}u_{ii}^2 - \frac{2}{L}u_{i\alpha}^2 + \frac{4L}{\varepsilon^2}u_{ii}u_{i\alpha}u_{\alpha}u^i \\
&\quad + \frac{L^4}{\varepsilon^4}A_{\alpha\alpha}A_{ii}u_{ht}u^h u^t + 2\frac{L}{\varepsilon^2}A_{\alpha\alpha}u_{ii}u_i u^i \\
&\quad + 2\frac{L}{\varepsilon^2}A_{ii}u_{\alpha\alpha}u_{\alpha}u^{\alpha} + \frac{4}{L^2}u_{i\alpha}u_{\alpha}u_i.
\end{aligned}$$

Hence

$$\begin{aligned}
(3.26) \quad \sum_{i,\alpha} w^{ii} A_{\alpha\alpha;ii} w_{\alpha\alpha} &= \frac{L^2}{\varepsilon^2}W \sum \varphi_h u^h + 2\frac{L^2}{\varepsilon^2} \sum w_{ii} u^i \varphi_i \\
&\quad - \frac{L}{\varepsilon^2}W \sum w^{ii} u_{ii}^2 - \frac{2}{L} \sum u_{ii}^2 \\
&\quad + \frac{L}{\varepsilon^2} \sum \left\{ 4u_{ii}^2 u_i u^i + 4u_{ii} u_i u^i + 2W w^{ii} u_{ii} u_i u^i \right\} \\
&\quad + \frac{L}{\varepsilon^2} \left\{ W\mathcal{W} \sum u_{ii} u_i u^i + 2\mathcal{W} \sum w_{ii} u_{ii} u_i u^i \right\}.
\end{aligned}$$

Recalling (3.20),

$$\sum \{4u_{ii}^2 u_i u^i + 4u_{ii} u_i u^i + 2W w^{ii} u_{ii} u_i u^i\} \leq Q,$$

and

$$W\mathcal{W} \sum u_{ii} u_i u^i + 2\mathcal{W} \sum w_{ii} u_{ii} u_i u^i \leq - \left\{ W\mathcal{W} \sum w_{ii} u_i u^i + 2\mathcal{W} \sum w_{ii}^2 u_i u^i \right\} + Q,$$

the second inequality of Lemma 2 follows from (3.26).

From (3.25) it follows that

$$\begin{aligned}
A_{\alpha\alpha;ii} - A_{ii;\alpha\alpha} &= \frac{L^2}{\varepsilon^2} A_{\alpha\alpha} w_{ii;h} u^h + \frac{2}{L} u_\alpha w_{ii;\alpha} \\
&\quad - \frac{L^2}{\varepsilon^2} A_{ii} w_{\alpha\alpha;h} u^h - \frac{2}{L} u_i w_{\alpha\alpha;i} \\
&\quad - \frac{L}{\varepsilon^2} A_{\alpha\alpha} u_{ii}^2 + \frac{4L}{\varepsilon^2} u_{ii} u_{i\alpha} u_\alpha u^i \\
&\quad + \frac{L}{\varepsilon^2} A_{ii} u_{\alpha\alpha}^2 - \frac{4L}{\varepsilon^2} u_{\alpha\alpha} u_{i\alpha} u_i u^\alpha.
\end{aligned}$$

Hence

$$\begin{aligned}
(3.27) \quad \sum w^{ii} (A_{\alpha\alpha;ii} - A_{ii;\alpha\alpha}) &= \frac{(n+2)L^2}{\varepsilon^2} \sum \varphi_i u^i \\
&\quad - \frac{L^2}{\varepsilon^2} \mathcal{W} \sum w_{\alpha\alpha;h} u^h - \frac{2}{L} \sum w^{ii} u_i w_{\alpha\alpha;i} \\
&\quad - \frac{nL}{\varepsilon^2} \sum w^{ii} u_{ii}^2 + \frac{L}{\varepsilon^2} \mathcal{W} \sum u_{ii}^2.
\end{aligned}$$

Since

$$-\frac{nL}{\varepsilon^2} \sum w^{ii} u_{ii}^2 \geq -\frac{L}{\varepsilon^2} Q$$

and

$$\frac{L}{\varepsilon^2} \mathcal{W} \sum u_{ii}^2 \geq \frac{L}{\varepsilon^2} \mathcal{W} \sum w_{ii}^2 - \frac{L}{\varepsilon^2} Q,$$

the first inequality of Lemma 2 follows from (3.27). \square

In view of Lemma 2, (3.22) can be rewritten in the form

$$\begin{aligned}
(3.28) \quad \sum w^{ij} W_{ij} &\geq \frac{L}{\varepsilon^2} \mathcal{W} \sum w_{ii}^2 + \frac{L}{\varepsilon^2} \mathcal{W} (W \sum w_{ii} u_i u^i + 2 \sum w_{ii}^2 u_i u^i) \\
&\quad - \frac{L^2}{\varepsilon^2} (W+6) \sum w_{\alpha\alpha;i} u^i + \mathfrak{R}_\varphi - \frac{L}{\varepsilon^2} Q,
\end{aligned}$$

where

$$(3.29) \quad \mathfrak{R}_\varphi =: -\frac{2L^2}{\varepsilon^2} \sum w_{ii} u^i \varphi_i + (n+6-W) \frac{L^2}{\varepsilon^2} \sum \varphi_\beta u^\beta + \sum \varphi_{\alpha\alpha}.$$

By (3.12), we have

$$(3.30) \quad \sum_\alpha w_{\alpha\alpha;k} = \sum A_{\alpha\alpha;k} w_{\alpha\alpha} - W \frac{\eta_k}{\eta}.$$

It follows from (3.23) that

$$\begin{aligned}
(3.31) \quad \sum_{\alpha} w_{\alpha\alpha;k} &= -W \frac{\eta_k}{\eta} - \frac{L^2}{\varepsilon^2} W u_{kk} u^k - \frac{2}{L} w_{kk} u_{kk} u_k \\
&= -W \frac{\eta_k}{\eta} + \frac{L^2}{\varepsilon^2} W w_{kk} u^k - \frac{L^2}{\varepsilon^2} W u^k \\
&\quad + \frac{2L^2}{\varepsilon^2} w_{kk}^2 u^k - \frac{2L^2}{\varepsilon^2} w_{kk} u^k.
\end{aligned}$$

Hence, by (3.9) and (3.20)

$$\begin{aligned}
(3.32) \quad -\frac{L^2}{\varepsilon^2} (\mathcal{W} + 6) \sum w_{\alpha\alpha;i} u^i &\geq -\frac{L}{\varepsilon^2} Q + \frac{L^2}{\varepsilon^2} W (\mathcal{W} + 6) \frac{\sum u^i \eta_i}{\eta} \\
&\quad - \frac{L}{\varepsilon^2} \mathcal{W} (W \sum w_{ii} u^i u_i + 2 \sum w_{ii}^2 u_i u^i).
\end{aligned}$$

Therefore, by inserting (3.32) into (3.28), we find that (3.13) can be written as

$$\begin{aligned}
(3.33) \quad 0 &\geq \frac{L}{\varepsilon^2} \mathcal{W} \sum w_{ii}^2 + W \sum w^{ij} \left(\frac{\eta_{ij}}{\eta} - 2 \frac{\eta_i \eta_j}{\eta^2} \right) \\
&\quad + \frac{L^2}{\varepsilon^2} W (\mathcal{W} + 6) \frac{\sum u^i \eta_i}{\eta} + \mathfrak{R}_{\varphi} - \frac{L}{\varepsilon^2} Q.
\end{aligned}$$

Without loss of generality, we may assume the cut-off function η satisfies $|D\eta|^2 \leq C\eta$ (otherwise we may replace η by η^2) and $|D^2\eta| \leq C$. Hence it follows

$$\begin{aligned}
&W \sum w^{ij} \left(\frac{\eta_{ij}}{\eta} - 2 \frac{\eta_i \eta_j}{\eta^2} \right) + \frac{L^2}{\varepsilon^2} W (\mathcal{W} + 6) \frac{\sum u^i \eta_i}{\eta} \\
&\geq -C \frac{W}{\eta} (|D^2\eta| + \frac{|D\eta|^2}{\eta}) \sum w^{ij} \sigma_{ij} - C \frac{L^2}{\varepsilon^2} \frac{W}{\eta} (\mathcal{W} + 1) \\
&\geq -\frac{L}{\varepsilon^2} Q,
\end{aligned}$$

where (3.8) is used in the last inequality. Therefore (3.33) can be written as

$$(3.34) \quad 0 \geq \frac{L}{\varepsilon^2} \mathcal{W} \sum w_{ii}^2 + \mathfrak{R}_{\varphi} - \frac{L}{\varepsilon^2} Q.$$

Lemma 3. *We have, at x_0 ,*

$$\mathfrak{R}_{\varphi} \geq -\frac{L}{\varepsilon^2} Q.$$

Proof. Recalling (2.6), we have

$$(3.35) \quad v_{\alpha} = 2u^h u_{h\alpha}.$$

Differentiating (3.16) gives

$$(3.36) \quad \varphi_\alpha = -(n+2) \frac{L^2}{\varepsilon^2} u^h u_{h\alpha} + \frac{f_\alpha}{f} - \frac{\nabla_\alpha(g \circ T)}{g \circ T},$$

$$(3.37) \quad \begin{aligned} \varphi_{\alpha\beta} &= -2(n+2) \frac{L^4}{\varepsilon^4} u^h u^t u_{h\alpha} u_{t\beta} - \frac{(n+2)L^2}{2} \frac{L^2}{\varepsilon^2} v_{\alpha\beta} + \frac{f_{\alpha\beta}}{f} \\ &\quad - \frac{f_\alpha f_\beta}{f^2} - \frac{\nabla_{\alpha\beta}^2(g \circ T)}{g \circ T} + \frac{\nabla_\alpha(g \circ T)}{g \circ T} \frac{\nabla_\beta(g \circ T)}{g \circ T}. \end{aligned}$$

Inserting (3.36) and (3.37) into (3.29), we obtain

$$(3.38) \quad \begin{aligned} \mathfrak{R}_\varphi &\geq 2 \frac{L^2}{\varepsilon^2} \sum w_{ii} \frac{\nabla_i(g \circ T)}{g \circ T} u^i - (n+6-W) \frac{L^2}{\varepsilon^2} \sum \frac{u^\alpha \nabla_\alpha(g \circ T)}{g \circ T} \\ &\quad - \sum \frac{\nabla_{\alpha\alpha}^2(g \circ T)}{g \circ T} - \frac{(n+2)L^2}{2} \frac{L^2}{\varepsilon^2} \sum v_{\alpha\alpha} - \frac{L}{\varepsilon^2} Q. \end{aligned}$$

Differentiating (3.35), we obtain

$$\begin{aligned} \sum v_{\alpha\alpha} &= 2 \sum \sigma^{th} u_{t\alpha} u_{h\alpha} + 2 \sum u^h u_{\alpha\alpha h} \\ &= 2 \sum \sigma^{th} u_{t\alpha} u_{h\alpha} + 2 \sum u^h A_{\alpha\alpha;h} - 2 \sum u^h w_{\alpha\alpha;h}. \end{aligned}$$

By (3.9), (3.10) and (3.20),

$$\sum \sigma^{th} u_{t\alpha} u_{h\alpha} = \frac{1}{L} \sum (u_{ii}^2 - u_{ii}^2 u^i u_i) \leq \frac{1}{L} Q.$$

From (3.23),

$$\sum u^i A_{\alpha\alpha;i} = -\frac{n+2}{L} u_{ii} u^i u_i \leq \frac{1}{L} Q.$$

Also, by (3.31),

$$\begin{aligned} -\sum u^k w_{\alpha\alpha;k} &= W \sum \frac{u^k \eta_k}{\eta} - \frac{1}{L} (W-2) \sum w_{kk} u_k u^k \\ &\quad + \frac{1}{L} W v - \frac{2}{L} \sum w_{kk}^2 u_k u^k \\ &\leq \frac{1}{L} Q. \end{aligned}$$

Therefore we have

$$(3.39) \quad \sum v_{\alpha\alpha} \leq \frac{1}{L} Q.$$

It then follows from (3.38)

$$(3.40) \quad \begin{aligned} \mathfrak{R}_\varphi &\geq \frac{2L^2}{\varepsilon^2} \sum w_{ii} \frac{\nabla_i(g \circ T)}{g \circ T} u^i \\ &\quad - (n+6-W) \frac{L^2}{\varepsilon^2} \sum \frac{u^i \nabla_i(g \circ T)}{g \circ T} \\ &\quad - \sum \frac{\nabla_{\alpha\alpha}^2(g \circ T)}{g \circ T} - \frac{L}{\varepsilon^2} Q. \end{aligned}$$

Now we compute $\nabla_\alpha(g \circ T)$ and $\sum \nabla_{\alpha\alpha}^2(g \circ T)$. By (2.16) we have

$$(3.41) \quad \nabla_\alpha(g \circ T) = g_k T_\alpha^k = g_\alpha w_{\alpha\alpha}.$$

By differentiating (2.16), we have

$$\begin{aligned} \sum \nabla_{\alpha\alpha}^2(g \circ T) &= \sum g_{kl} T_\alpha^k T_\alpha^l + \sum g_k \nabla_\alpha T_\alpha^k \\ &= \sum g_k A^{kl} w_{l\alpha;\alpha} + \sum g_{\alpha\alpha} w_{\alpha\alpha}^2 - \sum g_k A_{k\alpha;\alpha} w_{\alpha\alpha}. \end{aligned}$$

Recalling that $A^{kl} = \delta_{kl}$ at x_0 , we have

$$A^{kl} w_{l\alpha;\alpha} = w_{k\alpha;\alpha} = w_{\alpha\alpha;k} + A_{k\alpha;\alpha} - A_{\alpha\alpha;k}.$$

By (3.30),

$$\begin{aligned} \sum \nabla_{\alpha\alpha}^2(g \circ T) &= \sum g_k w_{\alpha\alpha;k} + \sum g_k (A_{k\alpha;\alpha} - A_{\alpha\alpha;k}) \\ &\quad + \sum g_{\alpha\alpha} w_{\alpha\alpha}^2 - \sum g_k A_{k\alpha;\alpha} w_{\alpha\alpha} \\ &= -W \sum g_k \frac{\eta_k}{\eta} + \sum g_{\alpha\alpha} w_{\alpha\alpha}^2 + \sum g_k (A_{k\alpha;\alpha} - A_{\alpha\alpha;k}) \\ &\quad + \sum g_k (A_{\alpha\alpha;k} - A_{k\alpha;\alpha}) w_{\alpha\alpha}. \end{aligned}$$

Using the second formula in Lemma 1, we get

$$(3.42) \quad \begin{aligned} \sum \nabla_{\alpha\alpha}^2(g \circ T) &= -W \sum g_k \frac{\eta_k}{\eta} + \sum g_{\alpha\alpha} w_{\alpha\alpha}^2 + \frac{L^2}{\varepsilon^2} (W-n) \sum w_{kk} u^k g_k \\ &\quad + \frac{L^2}{\varepsilon^2} (W - \sum w_{\alpha\alpha}^2) \sum u^k g_k. \end{aligned}$$

Inserting (3.41) and (3.42) into (3.40), we then obtain

$$(3.43) \quad \begin{aligned} (g \circ T) \mathfrak{R}_\varphi &\geq W \sum g_k \frac{\eta_k}{\eta} + \frac{2L^2}{\varepsilon^2} \sum w_{kk}^2 g_k u^k \\ &\quad - \frac{6L^2}{\varepsilon^2} \sum w_{kk} u^k g_k - \sum g_{\alpha\alpha} w_{\alpha\alpha}^2 \\ &\quad - \frac{L^2}{\varepsilon^2} (W - \sum w_{\alpha\alpha}^2) \sum u^k g_k - \frac{L}{\varepsilon^2} Q. \end{aligned}$$

By (3.5),

$$\begin{aligned}
(3.44) \quad \sum g_k \frac{\eta_k}{\eta} &= L \sum (\sigma^{ij} + \frac{L^2}{\varepsilon^2} u^i u^j) g_i \frac{\eta_j}{\eta} \\
&= \frac{L}{\eta} (\sum \sigma^{ij} g_i \eta_j + \frac{L^2}{\varepsilon^2} (\sum g_i u^i) (\sum \eta_j u^j)).
\end{aligned}$$

We have

$$\sum \sigma^{ij} g_i \eta_j = \langle Dg, D\eta \rangle \leq C,$$

where D is the normal derivative in \mathbb{R}^n and $\langle \cdot, \cdot \rangle$ denotes the standard Euclidean metric. Similarly, $\sum \sigma^{ij} u_i g_j = \sum u^j g_j$, $\sum \sigma^{ij} u_i \eta_j = \sum u^j \eta_j$ and $\sum \sigma^{ij} g_i g_j$ are all bounded by a universal constant C . Hence from (3.44),

$$(3.45) \quad \sum g_k \frac{\eta_k}{\eta} \geq -\frac{L}{\varepsilon^2} \frac{C}{\eta}.$$

Employing (3.9) and (3.20),

$$(3.46) \quad (u^k)^2 = \frac{\varepsilon^2}{L^3} u_k u^k \leq \frac{\varepsilon^2}{L^3},$$

for any given k . Using (3.10) then (3.9), we have

$$\sum \sigma^{ij} g_i g_j = \frac{1}{L} (\sum g_i^2 - \frac{L^3}{\varepsilon^2} (\sum u^i g_i)^2).$$

It implies

$$\begin{aligned}
(3.47) \quad \sum g_i^2 &= L \sum \sigma^{ij} g_i g_j + \frac{L^3}{\varepsilon^2} (\sum u^i g_i)^2 \\
&\leq C \frac{L^3}{\varepsilon^2}.
\end{aligned}$$

By (3.46) and (3.47) it follows that $|g_k u^k| \leq C$. Hence

$$(3.48) \quad \sum w_{kk}^2 g_k u^k \geq -CW^2$$

and

$$(3.49) \quad \sum w_{kk} u^k g_k \leq CW.$$

Moreover, in view of (3.8) and (3.9),

$$\sigma_{ii} = L + \frac{L^3}{\varepsilon^2} u_i u^i \leq C \frac{L}{\varepsilon^2},$$

for any given i . Consequently,

$$(3.50) \quad \sum g_{\alpha\alpha} w_{\alpha\alpha}^2 \leq |D^2 g| \sum \sigma_{\alpha\alpha} w_{\alpha\alpha}^2 \leq C \frac{L}{\varepsilon^2} W^2.$$

By virtue of (3.45), (3.48), (3.49) and (3.50), we obtain from (3.43) that

$$\begin{aligned}\mathfrak{R}_\varphi &\geq -\frac{L}{\varepsilon^2(g \circ T)}Q \\ &\geq -\frac{L}{\varepsilon^2}Q.\end{aligned}$$

This completes the proof. \square

By Lemma 3 and (3.34), we get, at x_0 ,

$$\begin{aligned}0 &\geq \frac{L}{\varepsilon^2}\mathcal{W}\sum w_{ii}^2 - C\frac{L}{\varepsilon^2}\left(1 + \frac{W}{\eta} + W^2 + \frac{W}{\eta}\mathcal{W}\right) \\ &\geq \frac{L}{\varepsilon^2}\mathcal{W}\frac{W^2}{n} - C\frac{L}{\varepsilon^2}\left(1 + \frac{W}{\eta} + W^2 + \frac{W}{\eta}\mathcal{W}\right).\end{aligned}$$

Multiplying $n\eta^2L$ to both sides of the above inequality, we obtain

$$\begin{aligned}(3.51) \quad 0 &\geq \frac{L^2}{\varepsilon^2}\mathcal{W}(H^2 - CH) - C\frac{L^2}{\varepsilon^2}(1 + H^2) \\ &\geq C\frac{L^2}{\varepsilon^2}\mathcal{W}H^2 - C\frac{L^2}{\varepsilon^2}(1 + H^2).\end{aligned}$$

Note that by (3.11),

$$(3.52) \quad \mathcal{W} \geq \sum_{k \geq 2} \frac{1}{\lambda_k} \geq \left(\prod_{k \geq 2} \frac{1}{\lambda_k}\right)^{\frac{1}{n-1}} \geq C\lambda_1^{\frac{1}{n-1}} \geq C\left(\frac{W}{n}\right)^{\frac{1}{n-1}},$$

where C is independent of ε . Hence from (3.51) we get

$$(3.53) \quad 0 \geq \frac{L^2}{\varepsilon^2}H^{2+\frac{1}{n-1}} - C\frac{L^2}{\varepsilon^2}(1 + H^2).$$

Hence $H \leq C$ at x_0 and this completes the proof of Theorem 1.

4. A COUNTEREXAMPLE TO THE LIPSCHITZ REGULARITY

In the last section we proved that the eigenvalues of DT_ε are uniformly bounded. In this section we give an example to show that the T_ε is not uniformly Lipschitz continuous for small $\varepsilon > 0$, i.e., the matrix DT_ε is not uniformly bounded, even though the densities f and g are smooth and positive, and the domain Ω^* is c-convex with respect to Ω .

Our counterexample will be obtained by finding a choice of f and g such that the monotonic optimal transport T_0 between them is not Lipschitz continuous. Even if we said that the convergence $T_\varepsilon \rightarrow T_0$ is not straightforward, we can prove that a uniform Lipschitz bound on T_ε would imply such a convergence, and hence the same bound on T_0 . Hence, if T_0 is not Lipschitz, then T_ε cannot be uniformly Lipschitz.

Lemma 4. *Suppose that the sequence of transports T_ε is uniformly Lipschitz. Then the whole family T_ε converges uniformly as $\varepsilon \rightarrow 0$ to the unique monotonic optimal transport for the cost $|x - y|$, which will be Lipschitz with the same Lipschitz constant.*

Proof. By Ascoli-Arzelà's Theorem, the uniform Lipschitz bound implies the existence of a uniform limit up to subsequences. Obviously this limit map T will be optimal for the limit problem, i.e. the Monge problem for cost $c(x, y) = |x - y|$ and will share the same Lipschitz constant as T_ε .

We only need to prove that T is monotonic along transport rays. Take $L_\varepsilon(x) = \sqrt{\varepsilon^2 + |T_\varepsilon(x) - x|^2}$: these maps are also uniformly Lipschitz and converge uniformly to $L(x) = |T_\varepsilon(x) - x|$. Let us denote by u_ε the potentials for the approximated problems and by u the potential for the limit problem. Due to the uniqueness of the Kantorovich potential u , since all the functions u_ε are 1-Lipschitz, we have $u_\varepsilon \rightarrow u$ uniformly. Moreover, $Du_\varepsilon \rightharpoonup Du$ and the convergence is actually strong (in L^2 , for instance) if restricted to the set $Tu = \{|Du| = 1\}$ (as a consequence of $|Du_\varepsilon| \leq 1$, which implies that we also have $\int_{Tu} |Du_\varepsilon|^2 \rightarrow \int_{Tu} |Du|^2$: this turns weak convergence into strong, and hence also implies pointwise, convergence).

The monotonicity of T is proven if one proves $DL \cdot Du \leq 1$, since the direction of the transport rays is that of $-Du$. This inequality is needed on the set of interior points of transport rays, which are exactly points where $|Du| = 1$. On these points we can use the weak convergence $DL_\varepsilon \rightharpoonup DL$ (weakly-* in L^∞) and the strong convergence $Du_\varepsilon \rightarrow Du$, which means that it is enough to get $DL_\varepsilon \cdot Du_\varepsilon \leq 1$, and then pass the inequality to the limit. This is the point where we use the uniform Lipschitz bound on T_ε : without such a bound we could not have the suitable weak convergence of DL_ε .

In order to estimate DL_ε , we use (2.8) and (2.4). We come back to the notation without the index ε , and write DL , thus getting

$$DL \cdot Du = -D_i u (T_j^i - \delta_{ij}) D_j u = L D_i u D_{ij}^2 u D_j u + |Du|^2 DL \cdot Du.$$

Then, we use (2.10) and (2.12) and the positivity of the matrix w_{ij} , to get

$$L D_i u D_{ij}^2 u D_j u \leq |Du|^2 (1 - |Du|^2).$$

This implies

$$(1 - |Du|^2) DL \cdot Du \leq |Du|^2 (1 - |Du|^2),$$

which provides $DL \cdot Du \leq |Du|^2 \leq 1$ (notice that, for fixed $\varepsilon > 0$, the norm of the gradient $|Du|$ is strictly less than 1, which allows to divide by $1 - |Du|^2$). \square

To construct the counterexample where T_0 is not Lipschitz, our idea is as follows. Let

$$(4.1) \quad \ell_a = \{(x, y) \text{ in } \mathbb{R}^2 \mid y = \sqrt{a}(x + 2 + a), x \in [-2 - a, 1]\}$$

be a family of line segments ℓ_a , where $a \in [0, 1]$. It is clear that the segments ℓ_a do not intersect with each other and $\cup_{a \in [0, 1]} \ell_a = \Delta_{ABC}$, where Δ_{ABC} denotes the triangle with vertices $A = (-3, 0)$, $B = (1, 4)$ and $C = (1, 0)$. Let

$$\begin{aligned} f &\equiv 1, \\ g &= 1 + \frac{1}{4}x + \eta(y) \end{aligned}$$

be two densities on Δ_{ABC} . We first show that there exists a smooth positive function η such that f, g satisfy the mass balance condition

$$(4.2) \quad \int_{\Delta_{P_a C Q_a}} f = \int_{\Delta_{P_a C Q_a}} g, \text{ for all } a \in [0, 1].$$

Here $P_a = (-2 - a, 0)$ and $Q_a = (1, (3 + a)\sqrt{a})$ are the endpoints of ℓ_a . We then prove that there is a Lipschitz function u , which is the potential function to Monge's problem in Δ_{ABC} , with the densities f, g given above. By (4.2) we can construct a measure preserving mapping T_0 , which pushes the density f to the density g , with $\{\ell_a\}$ as its transfer rays. Using the potential u and the duality we show that T_0 is the optimal mapping of Monge's problem. By reflection in the x -axis, we extend T_0 to the triangle $\Delta_{ABB'}$, where $B' = (1, -4)$ is the reflection of B . Then T_0 is not Lipschitz at the interior point $(-2, 0)$.

Lemma 5. *There exists a smooth positive function η , such that (4.2) holds. This function satisfies $\eta(y) = O(y^2)$ as $y \rightarrow 0$.*

Proof. By direct computation,

$$\begin{aligned} \int_{\Delta_{P_a C Q_a}} f &= \frac{1}{2}\sqrt{a}(3 + a)^2, \\ \int_{\Delta_{P_a C Q_a}} g &= \int_{-2-a}^1 \int_0^{\sqrt{a}(x+2+a)} \left(1 + \frac{1}{4}x + \eta(y)\right) dy dx \\ &= \frac{\sqrt{a}}{24}(3 + a)^2(12 - a) + \int_{-2-a}^1 \int_0^{\sqrt{a}(x+2+a)} \eta(y) dy dx. \end{aligned}$$

In order that (4.2) holds, we need

$$(4.3) \quad \frac{1}{24}a^{3/2}(3 + a)^2 = \int_{-2-a}^1 \int_0^{\sqrt{a}(x+2+a)} \eta(y) dy dx.$$

Differentiating (4.3) with respect to a , we have

$$\frac{a}{24} (9 + 7a) (3 + a) = \int_{-2-a}^1 (x + 2 + 3a) \eta(\sqrt{a}(x + 2 + a)) dx$$

which is equivalent to

$$(4.4) \quad \frac{a^2}{24} (9 + 7a) (3 + a) = \int_0^{(3+a)\sqrt{a}} (t + 2a\sqrt{a}) \eta(t) dt.$$

In order to find η satisfying (4.3) for all $a \in [0, 1]$, we only need to solve (4.4), since the equality in (4.3) is true for $a = 0$.

Let us introduce

$$(4.5) \quad y = (3 + a) \sqrt{a}.$$

It is clear that y is a strictly increasing function of a . Let $a(y) = O(y^2)$ be the inverse function of (4.5). Differentiating (4.4) in y and using $a_y = \frac{2\sqrt{a}}{3(a+1)}$, we obtain

$$\frac{\sqrt{a}}{36} (27 + 45a + 14a^2) = \frac{3(1+a)^2}{2\sqrt{a}} \eta(y) + \int_0^y \eta(t) dt,$$

Taking derivative again, we obtain

$$(4.6) \quad \eta'(y) + \frac{q(a(y))}{y} \eta(y) = yp(a(y)),$$

where

$$\begin{aligned} q(a) &= \frac{(5a-1)(3+a)}{3(1+a)^2}, \\ p(a) &= \frac{27 + 135a + 70a^2}{162(1+a)^3(3+a)}. \end{aligned}$$

Solving (4.6), one finds an explicit formula for η :

$$(4.7) \quad \eta(y) = \int_0^y t p(a(t)) \exp\left(-\int_t^y \frac{q(a(\tau))}{\tau} d\tau\right) dt.$$

It is clear that

$$-1 \leq q(a(y)) \leq 0 \text{ if } |y| \ll 1.$$

Hence

$$\begin{aligned} 0 \leq \eta(y) &\leq C \int_0^y t \exp\left(\int_t^y \frac{1}{\tau} d\tau\right) dt \\ &\leq Cy^2. \end{aligned}$$

From (4.7) it follows that

$$\begin{aligned}
(4.8) \quad \eta(y) &= \int_0^y t p(a(t)) \exp\left(-\frac{1}{2} \int_{a(t)}^{a(y)} \frac{5a-1}{a(1+a)} da\right) dt \\
&= \frac{\sqrt{a}}{324(a+1)^3} \int_0^a \frac{3(s+1)(27+135s+70s^2)}{\sqrt{s}} ds \\
&= \frac{a(10a^3+41a^2+54a+27)}{54(a+1)^3}.
\end{aligned}$$

In the last two equalities, a is the function of y determined by (4.5). Therefore η is positive and smooth and satisfies the required conditions. \square

Remark 1. From (4.5), we can explicitly write

$$a(y) = h(y) + \frac{1}{h(y)} - 2,$$

where

$$h(y) = \sqrt[3]{\sqrt{\frac{1}{4}y^4 + y^2} + \frac{1}{2}y^2 + 1}.$$

It is clear that $a(y)$ is a smooth even function.

Lemma 6. There exists a function $u : \Delta_{ABC} \rightarrow \mathbb{R}$ satisfying

$$|u(p) - u(q)| \leq |p - q|, \quad \forall p, q \in \Delta_{ABC},$$

and equality holds if and only if both p and q lie on a common segment ℓ_a .

Proof. We will construct a function $u : \Delta_{ABC} \rightarrow \mathbb{R}$, which decreases linearly along all ℓ_a .

For $(x, y) \in \Delta_{ABC}$, let $a = a(x, y)$ be the solution of the equation

$$(4.9) \quad y = \sqrt{a}(a + 2 + x).$$

Hence $(x, y) \in \ell_a$. Differentiating (4.9) with respect to x and y respectively, we get

$$(4.10) \quad 0 = \frac{a_x}{2a}y + \sqrt{a}(a_x + 1)$$

and

$$(4.11) \quad 1 = \frac{a_y}{2a}y + \sqrt{a}a_y.$$

It follows by (4.10) and (4.11) that

$$(4.12) \quad a_y + \frac{a_x}{\sqrt{a}} = 0$$

provided $a(x, y) \neq 0$.

On the other hand, for $(x, y) \in \Delta_{ABC}$, the direction vector of the line segment ℓ_a passing through (x, y) is given by

$$(4.13) \quad \nu(x, y) = (\nu_1, \nu_2) = -\frac{\left(1, \sqrt{a(x, y)}\right)}{\sqrt{1 + a(x, y)}}.$$

Hence, by (4.12),

$$(4.14) \quad \partial_y \nu_1 - \partial_x \nu_2 = \frac{1}{2(1+a)^{3/2}} \left(a_y + \frac{a_x}{\sqrt{a}} \right) = 0,$$

provided $a(x, y) \neq 0$.

Fix a point $P = (-2, 1)$. Let

$$\begin{aligned} \gamma(t) &= \gamma_X(t) \\ &= (t(x+2) - 2, 1 - t(1-y)), \end{aligned}$$

$t \in [0, 1]$. Then γ is the segment joining P and $X = (x, y) \in \Delta_{ABC}$. Set

$$u(x, y) = (x+2) \int_0^1 \nu_1(\gamma(t)) dt + (y-1) \int_0^1 \nu_2(\gamma(t)) dt.$$

We claim that u satisfies

$$(4.15) \quad Du(x, y) = \nu(x, y) \text{ on all segments } \ell_a.$$

Indeed, for any point $X_0 = (x_0, y_0) \in \Delta_{ABC}$ with $a(x_0, y_0) \neq 0$, by (4.14) we have

$$(4.16) \quad \begin{aligned} u_x(x_0, y_0) &= \int_0^1 \nu_1(\gamma_0(t)) dt + (x_0+2) \int_0^1 t \partial_x \nu_1(\gamma_0(t)) dt \\ &\quad + (y_0-1) \int_0^1 t \partial_x \nu_2(\gamma_0(t)) dt \\ &= \int_0^1 \nu_1(\gamma_0(t)) dt + \int_0^1 t \frac{d}{dt} \nu_1(\gamma_0(t)) dt \\ &= \int_0^1 \frac{d}{dt} (t \nu_1(\gamma_0(t))) dt = \nu_1(x_0, y_0), \end{aligned}$$

where $\gamma_0 = \gamma_{X_0}$ and we used $\partial_x \nu_2 = \partial_y \nu_1$. Similarly, we have

$$u_y(x_0, y_0) = \nu_2(x_0, y_0).$$

Taking limit, we see that (4.15) also holds on the segment $\ell_a \mid_{a=0}$.

As ν is a unit vector, hence from (4.15) we have

$$|u(p) - u(q)| \leq |p - q|, \quad \forall p, q \in \Delta_{ABC},$$

and equality holds if and only if both p and q lie on a common segment ℓ_a . This completes the proof. \square

As in [8, 32], one can show by Lemma 5 that there is a unique measure preserving map T_0 from (f, Δ_{ABC}) to (g, Δ_{ABC}) such that $T_0(p)$ and p lie in a common ℓ_a for all $p \in \Delta_{ABC}$, and satisfies the monotonicity condition

$$(T_0(p) - T_0(q)) \cdot (p - q) \geq 0 \quad \forall p, q \in \ell_a.$$

With the help of and Lemma 6, we prove that this T_0 is indeed optimal. This fact is classical in optimal transport theory, but we show it in details for the sake of completeness.

Lemma 7. *T_0 is an optimal mapping in the Monge mass transportation problem from (f, Δ_{ABC}) to (g, Δ_{ABC}) .*

Proof. Recall that the total cost functional is given by

$$\mathcal{C}(s) = \int_{\Delta_{ABC}} f(z) |z - s(z)| dz,$$

where $s \in \mathcal{S}$, the set of measure preserving maps from (f, Δ_{ABC}) to (g, Δ_{ABC}) ; and the Kantorovich functional is defined as

$$I(\psi, \varphi) = \int_{\Delta_{ABC}} f\psi + \int_{\Delta_{ABC}} g\varphi,$$

where (ψ, φ) are function pairs in the set

$$\mathcal{K} = \{\psi(x) + \varphi(y) \leq |x - y| \quad \forall x, y \in \Delta_{ABC}\}.$$

For all $s \in \mathcal{S}$ and $(\psi, \varphi) \in \mathcal{K}$, we have

$$\begin{aligned} (4.17) \quad I(\psi, \varphi) &= \int_{\Delta_{ABC}} f(z) \psi(z) dz + \int_{\Delta_{ABC}} f(z) \varphi(s(z)) dz \\ &\leq \int_{\Delta_{ABC}} f(z) |z - s(z)| dz \\ &= \mathcal{C}(s). \end{aligned}$$

That is

$$\sup_{\mathcal{K}} I(\psi, \varphi) \leq \inf_{\mathcal{S}} \mathcal{C}(s).$$

Let u be the function constructed in the proof of Lemma 6, and let $v = -u$. Then we have $(u, v) \in \mathcal{K}$. As $T_0(p)$ and p lie on the same line segment, Lemma 6 implies

$$u(z) - u(T_0(z)) = |z - T_0(z)|.$$

So the inequality in (4.17) becomes equality provided $(\psi, \varphi) = (u, v)$ and $s = T_0$. Therefore

$$\mathcal{C}(T_0) = I(u, v) \leq \sup_{\mathcal{K}} I(\psi, \varphi) \leq \inf_{\mathcal{S}} \mathcal{C}(s).$$

Hence T_0 is optimal and the segments ℓ_a are transfer rays of Monge's problem. \square

Let $B' = (1, -4)$ be the reflection of the point B in the x -axis and let $\Omega = \Omega^* = \Delta_{ABB'}$. Extend the functions f, g to Ω such that they are symmetric with respect to the x -axis. From the proof of Lemma 5, one sees that f, g are smooth and satisfy the mass balance condition (1.2). The fact that η is quadratic close to 0 shows that it can be reflected as a C^2 function, and Remark 1 shows that it is indeed smooth. It is also known [26] that Ω and Ω^* are c -convex with respect to each other (for the cost function c_ε , $0 \leq \varepsilon \leq 1$).

Also extend T_0 to Ω so that it is symmetric with respect to the x -axis. By the uniqueness of monotone optimal mappings [17], T_0 is an optimal mapping of Monge's problem from (f, Ω) to (g, Ω) .

We claim that T_0 is not Lipschitz continuous at the point $q_0 = (-2, 0)$. Let $D_{a,\delta}$ be the strip in Δ_{ABC} between the segments ℓ_a and $\ell_{a+\delta}$, and let $q_\sigma = (-2, \sigma)$ be the intersection of ℓ_a with the line $\{x = -2\}$, where $\delta, \sigma > 0$ are constants. Let $T_0(q_\sigma) = (x_\sigma, y_\sigma)$. As T_0 is measure preserving, we have (see the construction of the optimal mappings in [8, 32])

$$\lim_{\delta \rightarrow 0} \frac{1}{\delta} \int_{D_{a,\delta} \cap \{x < -2\}} f(x, y) dx dy = \lim_{\delta \rightarrow 0} \frac{1}{\delta} \int_{D_{a,\delta} \cap \{x < x_\sigma\}} g(x, y) dx dy.$$

That is

$$\int_{-2-a}^{-2} (x+2+3a) dx = \int_{-2-a}^{x_\sigma} (x+2+3a) \left(1 + \frac{1}{4}x + \eta(\sqrt{a}(x+2+a))\right) dx.$$

Making the change $t = 2 + a + x$, we obtain

$$\int_0^a (t+2a) dt = \int_0^{x_\sigma+2+a} (t+2a) \left(\frac{1}{2} + \frac{t-a}{4} + \eta(\sqrt{a}t)\right) dx$$

Since both $(t-a)$ and $\eta(\sqrt{a}t)$ tend to 0 when $t, a \rightarrow 0$ (recall that $\eta(t) = O(t^2)$), they are negligible in front of the constant $\frac{1}{2}$. This implies that, for small a , we should have

$$(4.18) \quad x_\sigma \geq -2 + (\sqrt{5} - 2)a.$$

Indeed, either $x_\sigma + 2$ does not tend to 0, in which case (4.18) is satisfied, or it tends to 0, in which case we can write, for small a ,

$$\int_0^a (t+2a) dt \leq \int_0^{x_\sigma+2+a} \frac{3}{4}(t+2a) dx.$$

Computing these integrals explicitly we get exactly the inequality (4.18).

On the other hand, by (4.1), we have $\sigma = a^{3/2}$. Note that $x(0) = -2$. Hence

$$(4.19) \quad \lim_{\sigma \rightarrow 0+} \frac{x(\sigma) - x(0)}{\sigma} \geq \frac{1}{4} \lim_{\sigma \rightarrow 0+} a^{-1/2} = \infty.$$

Our claim follows.

As $q_0 = (-2, 0)$ is an interior point of $\Delta_{ABB'}$, we have thus constructed positive, smooth densities f, g , and c -convex domains $\Omega = \Omega^* = \Delta_{ABB'}$, such that the associated optimal mapping T_0 is not Lipschitz at interior points.

As the triangle $\Delta_{ABB'}$ is c -convex with respect to each other, the optimal mapping T_ε is smooth [26]. By Lemma 4, one has $T_0 = \lim_{\varepsilon \rightarrow 0} T_\varepsilon$, and the above example shows that T_ε is not locally, uniformly Lipschitz continuous as $\varepsilon \rightarrow 0$.

5. APPLICATIONS AND PERSPECTIVES

The regularity problem for the Monge cost is very natural in transport theory and very difficult. For the moment, even the implication $f, g \in C^\infty \Rightarrow T_0 \in C^0$ in a convex domain is completely open. The transport T_0 , among all the optimal transports for the cost $|x - y|$ (for which there is no uniqueness), is likely to be the most regular and the easiest to approximate.

The present paper presented a strategy inspired by the previous results introduced in [26] to get Lipschitz bounds, i.e. L^∞ bounds on the Jacobian. Yet, it only allows for some partial bounds, and the counter-example of Section 4 shows that a Lipschitz result is not possible. However, in the same counter-example, the monotonic transport T_0 is a continuous map, and the point where a non-Lipschitz behavior is observed shows anyway the behavior of a $C^{0, \frac{2}{3}}$ map. Thus, it is still possible to hope for continuous, or even Hölder, regularity results on T_0 .

We stress that these results could also be applied to the regularity of the transport density. The transport density is a notion which is specifically associated to the transport problem for the Monge cost (see [17]): it is a measure σ which satisfies

$$(5.1) \quad \begin{cases} \operatorname{div} \cdot (\sigma Du) = f - g & \text{in } \Omega \\ |Du| \leq 1 & \text{in } \Omega, \\ |Du| = 1 & \text{a.e. on } \sigma > 0, \end{cases}$$

together with the Kantorovich potential u .

Several weak regularity results have been established, starting from the absolute continuity of σ if either f or g are absolutely continuous, till the L^p estimates $f, g \in L^p \Rightarrow \sigma \in L^p$ (see [17, 1, 13, 14, 28]).

An explicit formula for σ in terms of optimal transport plans or maps is available (we will not develop it here, see [1]) and most possible strategies for the regularity of the transport density need some continuity of the corresponding optimal transport. Yet, one of the advantages of working with σ is that any optimal transport T produces the same density σ . This allows for choosing the most regular one, for instance T_0 , but requires

anyway some regularity on it. Here is where our analysis comes into play (without, unfortunately, providing any exploitable result). But there are other features of the transport density that one could take advantage of: from the fact that it only depends on the difference $f - g$, one can decide to add any common density to both measures. For instance, if f and g are smooth densities with compact support on \mathbb{R}^n , it is always possible to add common background measure on a same convex domain Ω including both the supports. Ω can be chosen as smooth as we want, and we can for instance take Ω to be a ball. Also, one can add another common density to f and g so as to get $g = 1$. This last trick allows to avoid some of the tedious computations of Section 3, since in this case $g(T)$ has not to be differentiated.

In any case, even with these simplifications, the continuity result is not available for the moments. Possible perspectives of the current research involve the use of these partial estimates to prove continuity.

Among the possible strategies

- Use the bounds on DT_ε to get estimates on the directions of the transport rays for the limit problem, and use them to estimate how much the disintegrations of f and g vary according to the rays. Using the fact that the monotonic optimal transport (in one dimension) continuously depends on the measures, one can hope for the continuity of T_0 .
- Use the fact that the bound on W gives an L^∞ bound on $\operatorname{div}(LDu)$ and, since L depends on $|Du|$, one faces a highly non-linear and highly degenerate elliptic PDE where the goal would be to get uniform continuity results on LDu . This recalls what has been recently done in very degenerate elliptic PDEs for traffic applications (see [29, 11]), but seems (much) harder because LDu is not a uniformly continuous function of Du .
- Write down some elliptic PDEs solved by some scalar quantities associated to T_ε , for instance by L , and use the bounds on the matrices A and w that have been proven here in order to apply De Giorgi-Moser arguments (or their wider generalizations, see [15] for a complete framework). Should it work, this would give Hölder continuity. Unfortunately, our attempts have not given any useful PDE so far.

All in all, up to the two-dimensional result of [19] (which requires disjoint and convex supports), the search for continuous optimal transports for the original cost of Monge is still widely open.

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